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Let's call it quits: Break-even effects in the decision to stop taking risks

ABSTRACT

'Chasing' behavior, whereby individuals, driven by a desire to break-even, continue a risky activity (RA) despite incurring large losses, is a commonly observed phenomenon. We examine whether the desire to break-even plays a wider role in decisions to stop engaging in financially motivated RA in a naturalistic setting. We test hypotheses, motivated by this research question, using a large dataset: 707,152 transactions of 5,379 individual financial market spread traders between September 2004 and April 2013. The results indicate strong effects of changes in wealth around the break-even point on the decision to cease a RA. An important mediating factor was the individual's historical long-term performance. Those with a more profitable trading history were less affected by a fall in cash-balance below the break-even point compared to those who had been less profitable. We observe that break-even points play an important role in the decision of non-pathological risk-takers to stop RAs. It is possible, therefore, that these non-pathological cognitive processes, when occurring in extrema, may result in pathological gambling behavior such as 'chasing'. Our dataset focuses on RAs in financial markets and, consequently, we discuss the implications for institutions and regulators in the effective management of risk taking in markets. We also suggest that there may be a need to consider carefully the nature and role of 'break-even points' associated with a broader range of non-financially-focussed risk taking activities, such as smoking and substance abuse.

Key words: Break-even effects, ceasing a risky activity, mental models

1 INTRODUCTION

Engaging in risky activities (RAs) is vital to success in many spheres. However, where behaviour related to RAs has been scrutinised (e.g., in financial market trading or gambling activity), rogue traders or pathological gamblers are found to continue taking large risks despite incurring heavy losses, often with devastating outcomes. For example, Nick Leason bankrupted Barings Banks by losing \$1,074m, Kwenku Adeboli lost UBS \$1.82bn and Jerome Kerviel lost Société Générale approximately \$5.75bn. 'Chasing losses' is also a characteristic behavior in problem gamblers and is a clinical criterion for diagnosing gambling disorders.⁽¹⁾ Thus, at least in problem gamblers, there is a resistance to stopping the RA and this resistance appears to be connected to a desire to break-even ⁽²⁻⁶⁾. Given the importance of successful engagement in a broad range of RAs, greater understanding of the wider impact of break-even points is needed.

Resistance to ceasing a RA, based on wealth changes around the break-even point, has clear parallels with the observation, drawn from cognitive psychological research, that changes in wealth around psychological reference points have a special role in the perception of risk and reward.⁽⁷⁻⁹⁾ However, reference point effects are usually examined in relation to decisions made during a RA (e.g. whether to opt for risky vs. certain alternatives), rather than in relation to the decision to cease a RA. Perhaps for this reason, the subject of reference points has tended to focus on "local" reference points, such as the current wealth. However, the break-even point refers to a "global" reference point, where the individual's accumulated return *since commencing the RA* changes from loss to profit (and vice versa). An individual's decision to cease a RA generally has greater and longer-term implications than the risky choices made during a RA. Consequently, it seems likely that global reference points play an important role. Indeed, as discussed later, even the risky choices within a RA can involve consideration of both shorter and longer-term reference points.⁽¹⁰⁾ These effects are not just restricted to financial decisions. For example, American football teams have been shown to make risk sensitive decisions for attaining first downs (short-term goals) and reaching parity (long-term goals).⁽¹¹⁾

To explore the role that the break-even point plays in the decision to stop a RA, we analyse the decisions of individuals who engage in trading on financial markets. By understanding the cognitive biases associated with a decision to stop a RA, we can better understand the general cognitive processes that guide such decisions. This is valuable, since pathological cognitive processes may well be rooted in the tails of the distribution of what we observe as normal cognitive processing.⁽¹²⁾ Consequently, we expect our analysis of traders' decisions to shed light on the normal cognitive processes that could, in certain individuals, encourage extreme risk-taking activity (e.g., rogue trading). This is important, since rogue trading alone cost leading banks \$194.8 billion in fines and provisions between 2008-2012, rising to \$267.5 billion between 2010-2014.^(13,14)

We undertake a large, longitudinal study, employing the 707,152 transactions of 5,379 individuals in a UK spread-trading market between September 2004 and April 2013. We use survival analysis to control for the exogenous factors that could impact their decisions to cease trading. Our methodology allows us to isolate and measure the impact of break-even effects. We also control for long-term performance feedback and other trading characteristics (e.g., trading frequency), as these may mediate the effect of more recent performance and the effect of changes in wealth around the break-even point.

Our results confirm, not surprisingly, that an individual's decision to cease a RA, is linked to losing money. More interestingly, the decision is significantly affected by cognitive bias. In particular, fear of either remaining in loss or falling below the break-even point, rather than the magnitude of actual loss, appears to best predict the decision to stop trading. An important mediating factor on the effect of falling into loss or breaking even was the individual's longer-term performance (i.e. profitability), which we argue may influence their self-confidence. Those whose trading had generally been profitable (i.e. more confident in their profit-making ability) were less affected by a fall in their cash-balance below the break-even point when compared to those who had more frequently been in net loss. Additionally, those who had a history of losses were more likely to stop trading having recently broken even (cf. those who

had generally been profitable). This reveals that in certain situations individuals may be more likely to stop trading having recently made a profit.

Our findings have broad implications for our understanding of the nature and impact of break-even points on risk-taking behavior and how cognitive bias can impact the decision to cease a RA. The results also aid our understanding of some of the non-pathological cognitive factors that could impact, and possibly interact with rogue trader behavior and pathological gambling behaviors. We discuss the important implications for those engaged in RAs, for those involved in regulating these activities and for the effective management of risk taking in markets.

1.1 Break-Even and House Money Effects

We follow common practice in defining the break-even point as the point of balance between accumulated loss and profit since beginning a RA.⁽¹⁵⁾ which we refer to as accumulated net loss and net profit. 'Reference points' have been observed to play an important role in decision-making.⁽⁹⁾ These reference points are usually defined by the current wealth, with no memory of the past. In other words, having made a profit (or loss) through a RA, an individual's new, greater (or lower), wealth following a particular decision can become a new 'reference point' from which gains and losses are subsequently measured. These points appear to be important since reductions in wealth from such reference points are perceived differently to increases of similar magnitude; a phenomenon known as loss aversion. Kahneman and Tversky developed prospect theory based on this idea, identifying different shaped value functions for gains above and losses below this reference point.⁽⁷⁻⁹⁾ These value functions reflect different risk-seeking/aversion behaviors when comparing risky gains and losses.

Prospect theory assumes that, when making a decision, choice information goes through an 'editing phase'. Thaler and Johnson proposed that in this phase, the experience of past losses could heighten the perception of the value associated with future gains that could eliminate those previous losses; a so-called 'break-even effect'.⁽¹⁰⁾ Equally, the perception of the (negative) 'value'

of future losses may be diminished if the individual has experienced previous gains, because the 'losses' would be covered by previous winnings; a so-called 'house-money effect'

Both these effects have been demonstrated in experiments and in naturalistic studies.⁽¹⁰⁾ For example, traders have been found to take more risk in the afternoon following morning losses; perhaps indicative of a break-even effect.⁽¹⁶⁾ On the other hand, more risk-taking has been observed in the afternoon following gains in the morning, indicative of the house money effect.⁽¹⁷⁾ More recently, studies have considered non-linearity in the effects of past performance on future risk-taking and different patterns for different types of trader.^(18,19) These differences could have arisen from differences in their trading style or from differences between their long-term gains and losses (not accounted for in these studies).

One of the important limitations of these real-world studies is that they have only examined a very short trading period (e.g., between the morning and afternoon). However, Thaler and Johnson's ideas would suggest that gains and losses over a longer timeframe could also be important in mental accounting.⁽¹⁰⁾ Indeed, we suspect that consideration of whether the individual has made a profit/loss since beginning the activity may well have an important effect on the decision to cease a RA. Consequently, we consider the impact of not only recent gains and losses (i.e. changes from local reference points) but also of the overall profit/loss status of the individual relative to their starting capital (i.e. the global reference point or the break-even point).

1.2 Chasing, Escalation of Commitment and the Break-even Effect.

Chasing to recoup losses is the most commonly reported diagnostic criteria for problem gambling, observed in 84.1% of disordered gamblers.⁽⁶⁾ Chasing behavior appears to be correlated with higher levels of impulsivity and has been found to be associated with increased activity in brain areas linked to expectation of reward and incentive-motivation.^(2,3) It is perhaps for this reason that near misses have been shown to play an important role in chasing behaviour in both human and animal studies.^(20,21)

The motivation to continue gambling following 'near wins' may stem from a hope that these herald an imminent 'change of luck'. A similarly hopeful outlook appears in the escalation of commitment to a failing course of action, a cognitive bias that occurs in general populations.⁽²²⁻
²⁴⁾ The phenomenon describes the tendency to maintain or increase investment in an activity despite facing negative outcomes. Meta-analysis reveals that a desire to maintain one's reputation (to justify one's previous decisions) is one of the strongest predictors of escalation behaviour.⁽²⁵⁾

Breaking-even (cf. making a loss) clearly provides a means of vindicating the original decision to engage in a RA. Therefore, an individual's hope that they can break-even or a confidence that they will remain profitable may play an important role in how changes in wealth affect their decision to continue a RA. Experiments into near wins reveal that, beyond the objective outcome (e.g., successive losses), a hope or confidence in reversing a losing sequence may be important. For example, consider an individual (A) who has generally made profit from a RA but who, as the result of one bad month, falls into loss by \$100 dollars. Contrast this with an individual (B) who has been engaging in the RA for a similar period but who has not achieved a profit in any month and has lost \$100 dollars this month. We might expect the former (cf. the latter) to be more hopeful about their abilities to get back into profit. Indeed, as we discuss in the following section, we believe that this self-confidence or *positive mental model* (PMM), developed by engaging in the RA, may play a key role in how recent changes in wealth are interpreted when deciding whether to cease a RA.

1.3 Longer-term performance and mental models

We suspect that individuals develop a mental model of their ability to succeed in a RA, developed by observing their own winning and losing events. A fall below the break-even point is expected to be a fairly salient event, and it is likely to be most painful to those who do not have confidence in their ability to make profit in the long run. For individuals who have developed a PMM, a fall below the break-even point may have less impact. Indeed, research reveals that earlier formed mental models can bias new information.⁽²⁶⁾ Distortion of new

information to align with earlier information may be explained by cognitive dissonance, the motivation to avoid internal conflict regarding the mental model and new information, a need for some certainty in the choice, a search for dominance, or via a theory of cognitive coherence.⁽²⁷⁻³³⁾ Whatever the cause of this alignment process, we expect a fall below the break-even point to have a greater effect on those who have developed a more negative mental model (NMM) of their own abilities to make future profit; since this new information simply confirms their expectations.

[Figure 1 approx here]

A movement around the break-even point from net loss to net profit, may also elicit different responses depending on the individual's mental model. Consider the individuals illustrated in Figure 1. Individuals A and C could have developed a more NMM of their ability to make profit compared to B and D at the point of their 23rd month of engaging in the RA. If this is true, then recent performance feedback may be interpreted in light of this mental model: we expect A to experience little surprise at remaining in loss after the 24th month. However, C, who has just moved from net loss to net profit following the 24th month may experience considerable positive affect. If this individual had an objective to break-even, which the literature on chasing behavior suggests is common in those who lose money gambling, they may be more likely to stop the RA after the 24th month (cf. A, who sees the results of the 24th month as consistent with their expectations).

For individuals who have developed a more PMM (i.e. B and D), this pattern might be reversed. Remaining in loss for two consecutive months is inconsistent with their previous experience. The result of month 24 may therefore be a salient event and could cause the individual to consider ceasing the RA. On the other hand, while moving from net loss to net profit was surprising for C, it may be less salient for D, since it merely aligns with their mental model. For D, the loss following the 23rd month could be interpreted as 'unlucky' and may not result in them ceasing the RA.

Overall, therefore, while both A and B face identical relative profits and C and D face identical relative losses, their differing mental models could result in them making different choices.

In summary, to understand why an individual may/may not disengage from a RA, we believe it is important to consider their mental model, developed from their long-term experiences. In particular, we predict that changes in wealth around break-even points may have a different meaning to individuals depending on their past experiences. This aligns with the conclusion drawn in section 1.1 that the perception of recent (local) gains/loss may be processed in relation to an individual's longer-term memory of their performance.

1.4 Hypotheses

We explore our suspicion that the break-even point may play a role in the decision to cease a RA by testing our first hypothesis:

H1: *The probability of ceasing a RA will increase when an individual's long-run net return falls below their break-even point.*

As discussed in section 1.3, we expect that a change in wealth that crosses the break-even point will be particularly salient. Prospect theory's value weighting function suggests that a fall from being in long-run profit to being in long-run loss is likely to be particularly painful. This could even be sufficiently painful to cause an individual to stop trading. Indeed, similar discontinuities at the break-even point of individual trades have been observed in the transactions used to close those trades.⁽³⁴⁾ We, therefore, suspect that there will be a sudden increase in an individual's likelihood of ceasing to engage in a RA if they move from long-run net profit to net loss.

While we expect the general pattern of Hypothesis 1 to hold, all else being equal, as indicated in sections 1.1 and 1.3, we expect a more complex pattern to occur depending on (a) recent changes that the individual may have experienced in the short-run profit/loss arising out of their RA around the break-even point, and (b) the individual's longer-term performance

experiences. We suspect that memory of longer-term performance will be most prominent in developing the individual's mental model and we expect that a fall from above to below the break-even point may be more salient to those whose past experiences have led to them to develop a more NMM; the salience being cushioned for individuals with a PMM. Consequently, we test Hypothesis 2:

H2: *Individuals with a more NMM are more likely to cease a RA (cf. those with a PMM) when they fall from above to below the break-even point.*

As discussed in Section 1.3, we suspect that those who have developed a more NMM may be more likely to be driven to engage in chasing behavior in order to break-even. Consequently, we expect that they would be more likely to cease the RA having achieved this goal than if they have just experienced consecutive periods in loss. We explore this view by testing Hypothesis 3:

H3: *Individuals with a more NMM are more likely to cease a RA when they break-even than if they remain in long-run net loss between consecutive periods.*

We suspect that individuals who have developed a PMM, may demonstrate the opposite pattern of behavior. In particular, consecutive transactions leaving them in net loss would challenge their current mental model and could be enough to lead them to cease the RA. However, a transaction causing a move from net loss to net profit may simply confirm their mental model, thus being of less salience and having less impact on their likelihood of ceasing the RA. Consequently, we test the following hypothesis:

H4: *Individuals with a more PMM are more likely to cease a RA when they remain in net loss between consecutive periods than if they break-even.*

Support for H1 would reveal evidence in favor of the notion that a change in wealth around the break-even point is particularly salient to individuals when deciding whether to cease a RA. Support for H2, 3 and 4 would suggest that memory of longer-term performance plays an important role in affecting how individuals interpret more recent information.

Importantly, this would suggest that the decision to cease a RA depends on the interaction between the individual's longer-term and shorter-term performance.

2 METHOD

2.1 Data

We obtained a dataset of the trading histories of 29,434 individual clients of a large UK retail brokerage. We focused on one of the most popular markets for which we also had access to tick level market price data, namely the FTSE 100 Rolling Futures market. We did not want activity in other markets to distort our analysis. Consequently, we only considered individuals who had restricted their trading to this one market and who had traded at some time in the period for which we had data, namely the 9th September 2004 to 17th April 2013. This resulted in a dataset of 5,379 individual spread traders and their corresponding 707,152 transactions. The data was aggregated into monthly summary statistics for each individual trader.

2.1.1 Transactions in retail spread trading markets

Spread trading allows individuals to speculate on the movement of an underlying security (e.g., indices, commodities). No ownership of the underlying security takes place and, in the UK, spread trading is not subject to capital gains tax. This is important, because investors have no reason to close trades or to cease trading for tax purposes (as is the case for investors in regular financial markets). Trades can be 'long' or 'short' (speculating that the market will rise or fall in price, respectively). Whether a profit or loss is made depends on the direction of the trade and the price change that takes place. For the FTSE 100 futures, profits/losses are defined as the change in price of the FTSE 100 multiplied by the stake. For example, a trader who suspects the FTSE 100 might rise from its current price of 6500 would *buy* the market with, say, a \$5 stake per point. This is equivalent to a \$32,500 position in the market. However, since spread trading is highly leveraged, the traders are only required to have enough money in their account to

cover 'the margin' (an amount which past market movements suggest could easily be lost), which in the case of the FTSE 100 is $150 \times \text{stake}$ (i.e. \$750).

If the current price is 6500 and it rises 5 points, the trader would have an unrealized profit of \$25. Since the margin is a reasonable proxy for the amount that the trader risks in each trade, the percent return can be calculated as the return over margin staked (i.e. $25/750 = 3.33\%$). The leverage is clearly illustrated in this case, since a 0.08% return (i.e. $5/6500$) on the underlying market has produced a 3.33% return on margin. If the FTSE 100 fell by 5 points to 6495 and the trader decided to close their position by *selling* the market at \$5 per point, they would realize a loss of $-\$25$ (or -3.33%).

Spread-traders' data is ideal to test our hypotheses for several reasons: First, they are retail (cf. institutional) investors. Therefore, their choices are likely to be more indicative of the behavior of the general population, rather than of professional traders who are trained to operate in risky environments. Second, spread-traders tend to focus on only a handful of markets, and often only one, which they actively trade on a daily basis (1.6 times per day on average in our dataset). Individuals engaged in more traditional modes of investment tend to trade far less actively, holding funds or portfolios of many different individual shares over a much longer time (months/years). As spread traders tend to focus on only a few markets, there are fewer exogenous factors that need to be controlled. In addition, as spread-traders generally trade very actively, we can gather a large amount of behavioral data over a relatively short time period. Furthermore, spread trading is highly leveraged. Consequently, individuals can easily move from being in accumulated net profit to net loss and vice versa over the course of very few trades.

2.2 Variables

2.2.1 Accumulated Net Profit/Loss since beginning trading

We calculate a number of variables related to an individual's (k) trading behavior since they began trading with the brokerage. We calculate statistics for every year-month, m , since they

began trading. Each individual may have a different number, N , of months they were actively trading, and therefore different numbers of observations, $d=1, 2, 3, \dots, N_{km}$.

For each month, m , we calculate k 's accumulated net profit or loss ($ANPL_{km}$) since they began trading. This is based on the sum of total profit/losses in each given month ($MonthProfitLoss_k^d$) to month m :

$$ANPL_{km} = \sum_{d=1}^{N_{km}} MonthProfitLoss_k^d \quad (1)$$

Since, $ANPL_{km}$ is calculated for every month that the individual was actively trading, the set of observations, $\mathbf{ANPL}_k = (ANPL_{k1}, ANPL_{k2}, \dots, ANPL_{kn})$, are the cumulative sum of monthly profit/losses since the individual began trading until month m .

We proposed in section 1.3 that if an individual's \mathbf{ANPL}_k had remained positive for the majority of months, they may feel more confident in their ability to make profits in the future. As a result, for each month, m , we count the number of months that \mathbf{ANPL}_k is in profit and in loss. $NetGain_{km}$ and $NetLoss_{km}$ are binary variables indicating months in which the trader's $ANPL_{km}$ was positive or negative in that month, m , as follows:

$$NetGain_{km} = \begin{cases} 1 & ANPL_{km} \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (2)$$

$$NetLoss_{km} = \begin{cases} 1 & ANPL_{km} < 0 \\ 0 & \text{Otherwise} \end{cases} \quad (3)$$

Using these variables, we calculate $GenerallyProfitable_{km}$: 1 if the trader's $ANPL_{km}$ had remained positive in the majority of months up to and including month m , and 0 otherwise:

$$GenerallyProfitable_{km} = \begin{cases} 1 & \left(\sum_{d=1}^{N_{km}} NetGain_k^d \right) > \left(\sum_{d=1}^{N_{km}} NetLoss_k^d \right) \\ 0 & \text{Otherwise} \end{cases} \quad (4)$$

In section 1.3 we highlighted the importance of the impact of changes in an individual's profit status, i.e. changing from positive $ANPL$ in month $m-1$ to negative $ANPL$ in month m or vice versa. This is captured by $StatusChange_{km}$: 1 if the trader's $ANPL$ changed sign in the current month compared to the previous month, and 0 otherwise, as follows:

$$StatusChange_{km} = \begin{cases} 1 & NetGain_{k(m-1)} \neq NetGain_{km} \\ 0 & Otherwise \end{cases} \quad (5)$$

In order to test hypotheses 2 to 4, it is necessary to allow for different effects of a change in wealth around the break-even point (i.e. $StatusChange_{km} = 1$) depending on whether the trader has been in net profit (i.e. $GenerallyProfitable_{km} = 1$) or in net loss (i.e. $GenerallyProfitable_{km} = 0$) more frequently in the past. We use $GenerallyProfitable_{km}$ as a proxy for an individual's mental model of their ability to be profitable in the future. The $NetLoss_{km}$ feature when used in conjunction with $StatusChange_{km} = 1$ indicates the type of status changes. Table I shows how the different combinations of these three features are used to indicate different events.

[Table I about here]

2.2.2 Return on Capital at Risk

Our hypotheses are specific to the valence of ANPL and changes from above and below the break-even point. However, we are also interested in how changes in magnitudes of gains and losses might affect the decision to stop trading. Since different traders will have different sizes of trading capital, we calculate an individual's accumulated capital at risk ($ACAR_{km}$) since beginning trading:

$$ACAR_{km} = \sum_{d=1}^{N_{km}} CapitalAtRisk_k^d \quad (6)$$

We then calculate each trader's accumulated net return on investment ($AROI_{km}$) as $AROI_{km} = ANPL_{km}/ACAR_{km}$. However, previous research suggests that a change in $AROI$ may have a different influence on the chance of a trader deciding to stop trading when they are in net gain or net loss.⁽¹⁷⁾ Therefore, we separate the ROI for those traders in long-run profit and in long-run loss in month m , as follows:

$$ProfitROI_{km} = NetProfit_{km} \times AROI_{km} \quad (7)$$

$$LossROI_{km} = NetLoss_{km} \times AROI_{km} \quad (8)$$

2.2.3 Other individual-related control factors

We control for other factors that might influence an individual's decision to stop trading. The first two relate to the returns and the volatility of those returns on capital invested during a given month; specifically, the mean ($Return_{km}$) and the standard deviation ($Volatility_{km}$) of their return on capital at risk per trade in a given month. We also calculate the mean stake size of a trade in a given month ($Stake_{km}$), because those who tend to stake more may do so because they believe they have more information and, hence, are less likely to stop trading that month. We also incorporate the number of trades placed in a given month ($Trades_{km}$) because higher trade frequency is generally associated with overconfidence and this may be associated with a lower likelihood of an individual deciding to stop trading. We also incorporate the average duration of trades closed in a given month, defined as the average time in minutes from the opening to the closing of each transaction for each position ($HoldTime_{km}$). Holding a position for longer may indicate greater confidence, as the individual spends more time actively holding risk in the market.

2.2.4 Market control factors

Our dataset begins in 2004 and ends in 2012. Consequently, it spans the recent financial crisis. In the FTSE 100 market, volatility was at its peak in October 2008. Notably, in September, Merrill Lynch was sold to Bank of America and in October, Lehman Brothers announced that they would file for bankruptcy. In response to these and other news shocks, the FTSE100 fell dramatically, leading to significant volatility in the market. Overall, in 2008 and 2009 price volatility was on average 1.84% and 1.12% per day, respectively, compared to a daily mean of 0.83% and a median of 0.69% from 2004 to 2013.

Market volatility could be intimidating to traders. Consequently, we controlled for these effects by including in our model both the mean and the standard deviation of daily market returns ($MarketReturn_{km}$ and $MarketVolatility_{km}$, respectively). We controlled for the time-period of the crisis, to capture any additional effects of the fear associated with this period that cannot be explained by the market conditions variables. In particular, we included a factor for

the year, the variable taking seven levels: '<2006' for any year prior to 2006, '2007' for 2007, '2008' for 2008, etc., and '2011+' for the years from 2011 onwards.

2.3 Time dependent survival analysis models

We employ survival analysis (SA) to test our hypotheses related to the effect of a variety of covariates on the likelihood that an individual decides to cease trading in a given month. SA allows the investigation of the probability distribution of an event's occurrence at time t given it did not occur before t (e.g. a trader ceasing to trade at t). SA has been applied in many fields, including political science, demography, systems analysis, economics and finance.⁽³⁵⁻⁴⁴⁾

There is no prior evidence concerning the probability distribution for the time until an individual stops trading. Consequently, we adopted the Extended Cox Proportional Hazard model (CPH) with time-varying covariates;⁽⁴⁵⁾ a powerful multiplicative regression SA model, which avoids potentially biased prior distribution assumptions and accounts for multiple risk factors simultaneously (i.e. covariates). It has been successfully adopted in many domains.^(46,47) Full details of the CPH model we employ are provided in appendix A.

To examine the factors which influence the time until an individual ceases to trade, we define the hazard rate $h(t, \mathbf{x}_k(t))$ as the instantaneous probability of individual k ceasing to trade at month m ($t=m$, conditional on the 'cease trading' event not taking place before t) where variable $\mathbf{x}_k(t)$ represents a set of time-varying characteristics (e.g. returns) for trader k . In particular, to test the hypotheses we explore how particular values of covariates affect an individual's hazard rate, compared to the baseline hazard (i.e. where covariates take baseline values, i.e. when $\mathbf{x}_k^l(t)$ equals zero); i.e. quantifying the effect of a range of factors on the risk of an individual ceasing to trade at a given time, t (e.g., in month m).

3. RESULTS

3.1 Descriptive Statistics

Table II displays descriptive statistics for all variables included in the model for each year between 2006 and 2010 and for the periods prior to 2006 and after 2010. The value of each

statistic in each period is compared with the average value for the entire dataset, excluding that period, to determine if the value is particularly extreme. The 'exit rate' shows the percentage of individuals whose last trade was recoded in a given period and this increased significantly in 2008 and 2009, with around 3 in 4 individuals stopping in 2009. Interestingly, traders' returns were fairly consistent throughout all the years, ranging from an average loss of -5.5% to -3.5% per trade; values consistent with research exploring day traders' profitability.⁽⁵⁰⁾ The consistency of traders' returns is not reflected in the underlying market returns, which had particularly significant negative average daily returns in 2008 (-0.2%). However, the volatility of trader returns was significantly higher in 2008, reaching around 14% compared to the 11.6% observed on average across the other periods. Interestingly, ROI was no worse in 2008 than at other times and marginally improved in 2009. Traders could limit the impact of volatility by reducing stake size but, surprisingly, there is little evidence of any reduction despite the increased volatility. Similarly, individuals could have reduced their trade frequency to reduce their risk exposure. However, in 2008 trade frequency increased, which echoes previous findings that individual investors in equity markets continued to trade actively throughout the crisis and did not reduce the risk of their investment portfolios.⁽⁵¹⁾ However, the fact that stake sizes remained constant and position holding times were lower between 2007 and 2009 suggests that the greater volatility increased the rate at which price changes met the traders' profit/loss expectations for position closure. These mean holding times should be considered alongside the knowledge that they follow a long-tailed distribution and that retail investors in these markets are actually more akin to day-traders than long term investors. Indeed, 69.9% of the traders in our sample had a median trade duration of less than one hour, 24.1% had a median holding time longer than one hour but less than 24 hours, and only 5.9% had a median holding time longer than 24 hours.

[Table II about here]

Overall, the descriptive statistics suggest that individuals were most likely to cease trading in 2008 and 2009. However, other than an increase in return volatility in 2008, profitability did not appear to be significantly worse during this period. Consequently, to examine

the factors that influenced individuals' decisions to cease trading, we examined the results of the time dependent SA models.

3.2 Survival Analysis Results

We first fitted a CPH model incorporating all the trader profitability, trader discipline and other trading and market characteristic covariates discussed in section 2.2. The results of estimating this model are presented in Table III.

Those who staked more, or traded more frequently, or held positions for longer (perhaps indicating greater confidence) tended to continue trading longer. In support of previous findings, our results show that there are different survival functions for individuals whose ROIs were in (a) profit and (b) loss, since they commenced trading.⁽¹⁷⁾ The coefficient for $\sqrt{\text{LossROI}}$ is significant and negative, indicating that the greater the loss incurred the greater the individual's chance of ceasing trading. However, the total net returns on investment for accounts in profit ($\sqrt{\text{ProfitROI}}$) is not significant, indicating that the amount of (positive) profit made by an individual does not affect their probability of ceasing trading.

Another interesting observation is that due to the salience of a change from above to below an individual's break-even point, a discontinuity in the survival function at the break-even point exists. Our first evidence for this is the strongly significant coefficient for $\ln \text{Loss}_{km}$. This coefficient suggests a dramatic, 9.77 times increase in the likelihood of an individual ceasing to trade if their ANPL_{km} at the end of a given month is a fraction less than zero (cf. when it is just greater than zero). This large effect size is revealed in Figure 2, which shows the change in likelihood of ceasing to trade when an individual's cumulative balance changes sign. The figure reveals that as individuals earn more money above the break-even point (zero on the x-axis) they have a gradual decrease in the likelihood of stopping trading. Similarly, although with a much greater effect, the more money an individual loses below the break-even point, the greater the likelihood of them stopping trading. This may not be surprising. However, the sudden discontinuity around the break-even point is striking. A small change in wealth from

above to below the break-even point leads to a dramatic increase in the likelihood of the individual stopping trading. These results support H1, that a significant increase in the probability of ceasing a RA will occur when an individual's accumulated net return falls below their break-even point. They also reveal that the functions are very different for those with positive and those with negative cumulative returns. It should be noted that the difference between the shapes of the curves above and below the break-even point have more than a passing resemblance to the curves of prospect theory with respect to gains and losses.

[Table III & Figure 2 about here]

We proposed that the size of the discontinuity in the survival function would depend on how recent changes around the break-even point were perceived in relation to the individual's longer-term memory of their success. We argue that this may be because those with more past success may develop a PMM and this could influence how they view changes in wealth around the break-even point (i.e. Hypotheses 2 - 4). In order to test these hypotheses, we examined the effects associated with *GenerallyProfitable_{km}* and *StatusChange_{km}* alongside *LossMonth_{km}* and the significant interactions (i.e. *GenerallyProfitable* × *LossMonth*)_{km}, (*GenerallyProfitable* × *StatusChange*)_{km}, (*LossMonth* × *StatusChange*)_{km} and (*GenerallyProfitable* × *LossMonth* × *StatusChange*)_{km}. We summarize these effects in Table IV, by showing the model's estimated hazards associated with each possible combination of *GenerallyProfitable_{km}*, *StatusChange_{km}* and *LossMonth_{km}*. Those traders who have experienced most periods of *ANPL_{km}* in net profit or loss we refer to as the PMM (*GenerallyProfitable_{km}* = 1) and NMM (*GenerallyProfitable_{km}* = 0) groups, respectively.

The first observation, unsurprisingly, is that those whose cumulative returns remain in profit from one month to the next are the least likely to cease the RA. Importantly, we find that the NMM group were more likely to cease trading when they moved from net profit to net loss in that month than if they experienced consecutive periods in loss (16.72 vs. 9.77, $\exp(\Delta\text{coef}) = 1.71$, $z = 10.95$, $p < .001$). This suggests that the pain of falling below the break-even point is more salient than the pain of remaining in net loss from one period to the next for the NMM

group. However, for the PMM group, there was no significant difference in the probability of ceasing to trade when they moved from net profit to net loss and when they experienced consecutive periods in net loss (7.53 vs. 6.03, $\exp(\Delta\text{coef}) = 1.25$, $z = 0.93$, $p = .353$). This supports our view that a more PMM, constructed from memory of longer-term performance, can cushion the effect of falling below the break-even point. Indeed, in support of Hypothesis 2, the NMM group exhibited more than double the likelihood of ceasing to trade when falling below the break-even point in a month compared to the PMM group (16.72 vs. 7.52, $\exp(\Delta\text{coef}) = 2.22$, $z = 5.51$, $p < .001$).

[Table IV approx here]

As shown in Table IV, individuals in the NMM group who were in net loss in the previous month, were almost eleven times more likely to stop trading if they moved into net profit in the current month, and almost ten times more likely to stop if they remained in net loss in the current month (compared to the baseline). While the direction of this difference supports Hypothesis 3, the difference was not significant (11.23 vs. 9.77, $\exp(\Delta\text{coef}) = 1.15$, $z = 1.04$, $p = .299$). However, we did observe support for Hypothesis 4. In contrast to the NMM group, the PMM group more likely to cease trading if they remain in net loss from one month to the next compared to moving from net loss in the previous month to net profit in the current month (6.04 vs. 2.32, $\exp(\Delta\text{coef}) = 2.60$, $z = 2.38$, $p < .05$). This difference between the NMM and PMM groups reveals how the decision to stop a RA appears to depend on an interaction between the memory of longer-term performance and recent outcomes, and particularly when those recent outcomes involve changes around the break-even point.

3.2.1 Alternative Definitions of Historical Profitability

We now extend our analysis over different definitions of historical profitability. The first change is that we now define those with a PMM/NMM as those who have experienced at least 75% and 90% of months where their accumulated net return was positive/negative (rather than experiencing at least 50% of months where their accumulated net return was positive/negative, as in the previous definition). We might infer that these traders have a stronger PMM/NMM

than those we identified using the previous definition. The results of the analyses employing these new definitions of PMM and NMM are presented in Table IV. They demonstrate that the general patterns discussed above persist. However, whatever the change in their cumulative net return from one month to the next, the overall likelihood of an individual ceasing trading decreases monotonically as the percentage of months in profit/loss since commencing trading increases. Consequently, we might infer that the stronger a trader's NMM or PMM the less likely they are to cease trading, whatever the change in their lifetime profit position from one month to the next.

In our introduction we discussed the fact that research has tended to focus on changes in value from 'local' reference points, rather than the more 'global' break-even point since beginning the RA. In the following analysis, for comparison, we examine 'local' break-even points based on recent changes in wealth. Instead of considering an individual's accumulated net return over all the months since they began trading up until the current month, we now employ a 'look-back window' to only consider accumulated net return in the most recent months prior to the current month. For this analysis we employed the definitions of PMM and NMM based on 90% of months in profit and 90% in loss, respectively. These definitions are employed as they should most clearly differentiate between those with a PMM and NMM, since we are only examining subsets of individuals at opposite extremes of the spectrum. We vary the look-back window size (between 6 months to 36 months) in order to examine how a shorter versus a longer history of more than 90% of months in net profit or loss might affect the likelihood of ceasing trading in the current month, given a change in accumulated net return (i.e. a change from negative to positive or positive to negative return over the whole look-back window). The results of this analysis are displayed in Figures 3(a-d). These figures show how the likelihood of ceasing to trade (indicated by the hazard rate estimated by CPH models) depends on the individual's mental model, whether they move from profit to loss or loss to profit in a given month and the look-back window size.

The first observation is that, having changed our definition of the PMM and NMM groups to increase the proportion of months in net profit and loss, respectively, during the look back window, from 50% to 90%, individuals in both the PMM and NMM groups were unlikely to stop trading having moved from net loss to net profit (hazard rate ≈ 0 for all), whatever the look-back window. The main difference here is that in our previous analysis the NMM group (based on their complete trading history) tended to stop trading when they passed the break-even point and made a profit. However, using our alternative definition of the NMM group based on their more recent trading history, they do not tend to cease trading in this situation. Consequently, it appears that the desire to stop trading when net returns become positive occurs when the individual experiences more than 50% of months when cumulative returns are negative *throughout their trading history*. However, this does not seem to be the case if individuals simply experience net losses in a large proportion of recent months, even if this proportion is as high as 90% and the period examined is as long as three years.

There are numerous possible explanations for why this might occur. For example, it could be that facing accumulated net losses for a large proportion of recent months produces such a strong NMM that cognitive biases are employed to explain away this negative information, to protect the individual from the cognitive dissonance. Another possibility is that there may be a selection bias resulting from this new definition. In particular, the types of personality associated with individuals in the NMM group defined by their facing net losses in more than 90% of recent months, may be different from those in the NMM group defined by their experiencing net losses in more than 50% of months since they began trading. It is certainly possible that someone who stubbornly remains trading over the last 36 months whilst experiencing net losses in 90% of those months could be very different from an individual who experiences just 50% or more of months of net losses since beginning trading. Clearly, therefore, this interesting finding requires more research to determine precisely the mechanisms behind these effects. In particular, it would be helpful to explore whether individuals in the NMM group defined as experiencing more than 90% of the most recent

months in net loss, tend to be more problem gambler types. Unfortunately, our data do not allow us to undertake such an analysis.

We also explore the contrasting behavior of the PMM and NMM groups, now defined in terms of their having experienced more than 90% of the most recent months in net profit or loss, when they move from net profit to loss. The results show that the NMM group are far more likely to stop trading compared to the PMM group, as was the case when we employed our previous definitions of the NMM and PMM groups. However, the results demonstrate that the probability of ceasing to trade is also affected by the period they experience a high proportion of months where their net returns are positive or negative. For the PMM group (Figure 3b), there is an upward trend, whereby the longer an individual experiences a high proportion of months in net profit the more likely they are to cease trading when their cumulative profit over the period becomes negative. Perhaps the longer the individual has been in profit, the more likely they are to perceive falling into loss as a signal of their luck changing or their strategy beginning to fail. It is also possible that the losses that end a long winning streak (e.g., after 36-months) are more emotionally impactful than the losses that end a shorter (e.g., 6-month) winning streak.

The opposite pattern appears for the NMM group (Figure 3d), defined as those individuals who have experienced more than 90% of the most recent months in loss. In particular, the longer the period these individuals experience a high proportion of months in net loss, the less they are likely to cease trading in a month when their cumulative return changes from positive to negative. As discussed above, it is uncertain whether there are important differences between the types of individual who continue trading for a long period (e.g., 36 months) and a short period (e.g. 6 months) despite their cumulative returns being negative for more than 90% of these months. It is certainly possible that the 36-month group could contain more problem gambler types than those in the 6-month group.

4 DISCUSSION

Our results consistently show that individuals do not only stop a RA once they have experienced heavy losses. Frequently, they stop when there is a risk of losing only a small amount of the original amount invested and sometimes are more likely to stop having recently made a net profit from the RA. Significantly, their decision to stop trading appears influenced by recent changes in their cumulative returns around the break-even point and this effect depends on the individuals' longer-term performance. We suspect that individuals form a mental model associated with their longer-term performance and this then influences their interpretation of newer information. In particular, our results suggest that those who develop a PMM over their entire trading history prior to a given month are less affected by break-even effects than those who develop a more NMM. This effect persisted when we limited analysis to those we inferred may have stronger PMM and NMM (i.e. those who had experienced 75% and 90% of months in net profit/loss throughout their trading history). Using these new definitions of PMM and NMM, the general patterns persist, except that the overall likelihood of ceasing to trade decreased monotonically as the percentage of months in profit/loss since commencing trading, increased. Suggesting that those who experience consistently profitable or unprofitable trading are less affected by global break-even effects.

We also found that more recent experiences of engaging in a RA have different effects on an individual's decision to stop participating in a RA. The longer the period an individual experiences 90% of months being in net profit, the more likely they are to stop trading if they incur losses that mean they fall below the local (break-even) reference point. On the other hand, the longer the period an individual experiences 90% of months being in net loss, the less likely they are to stop trading when they incur losses resulting in a fall below the local (break-even) reference point.

When taken together, the results exploring both global and local reference points suggest that when stronger NMM are developed (based on the trader experiencing a large proportion (90%) of a large number of months in loss) the effect of both global and local reference points are reduced. However, while those with stronger PMM appear to be less

affected by global break-even effects, they appear to be more affected by local break-even effects.

4.1 Mental models, breaking-even and disengaging from a risk-taking activity

Our key finding is that the decision to discontinue a RA can be strongly affected by changes in net returns around the break-even point (which we refer to as their global reference point). When individuals are in accumulated net profit, irrespective of the magnitude of that profit, they are very unlikely to stop a RA. However, as soon as their accumulated return changes from net profit to net loss, they are almost 10 times more likely to stop than when they were in profit. Furthermore, this large effect size linked to falling into net loss could be mediated by the individual's longer-term performance. For example, those who had experienced more months when their accumulated returns were negative (NMMs), were more than 15 times more likely to discontinue than the baseline risk¹. Whereas PMMs were only seven times more likely to discontinue than the baseline risk. This suggests that the decision to stop a RA is affected by cognitive biases related to a change in cumulative returns around the break-even point but that this effect can be mediated by the memory of longer-term performance across the individual's trading history. This is entirely consistent with Thaler and Johnson's suggestion that gains and losses over a longer timeframe could also be important in mental accounting.⁽¹⁰⁾

Perhaps unsurprisingly, those individuals who had experienced more months where their cumulative returns were positive were more likely to discontinue the RA if they experienced two consecutive months where their accumulated returns were negative than if their accumulated returns moved them from loss in one month to profit in the following month. However, the opposite was true for those who experienced more months with negative accumulated returns. These individuals were more likely to cease trading when they changed

¹ Baseline group: individuals with a negative mental model and who experienced net profit in both the previous and current month and all other covariates are equal to zero.

from net accumulated loss in one month to net accumulated profit in the following month (cf. when they remained in accumulated loss for two consecutive months). This evidence contradicts the assumption that individuals only stop undertaking a RA when they have incurred significant loss. This finding is also consistent with chasing behavior, since it suggests that individuals may only continue a RA in order to win back their previous losses. Once they achieve their objective of breaking even they cease the RA, otherwise they continue. Our results are also consistent with prospect theory's value function (i.e. risk averse/preferring in the domains of gains/losses) and with the 'break-even effect', whereby individuals have a tendency to continue to take risks, despite consecutive periods in loss, in the hope that they will soon break-even.

The results demonstrate that the decision to discontinue a RA is influenced by cognitive biases and that such effects can be modulated by an individual's longer-term performance. The later, we believe, may influence their confidence in their abilities related to the RA. This is important, since it may help to explain the mechanisms by which overconfidence can affect trader survival. For example, studies reveal that overconfident traders can persist in markets despite competition from rational traders.⁽⁵²⁻⁵⁴⁾ Our results suggest that this could arise because of the greater resilience of confident individuals when they face losses. Additionally, our findings may further explain the contradictory conclusions drawn by previous real-world studies of this phenomenon, since these previous studies did not examine the mediating effects of longer-term performance on the break-even and house money effects.^(16,17)

We show that cognitive biases around the break-even point can impact the decision to disengage from a RA. This reveals that, aside from behavioral addiction (e.g., in pathological gambling), non-pathological cognitive psychological processes can also lead to a continuation of a RA when in loss.⁽⁵⁵⁻⁵⁷⁾ This is important, since abnormal behavior often appears to stem from exaggerations of normal mental processes.⁽¹²⁾ We found that those we assumed to hold a more PMM (cf. NMM) were less likely to discontinue a RA following two consecutive periods where their accumulated returns were negative. If a more PMM is associated with overconfidence, then

our results fit well with the overconfidence hypothesis of chasing behavior and suggest that some degree of chasing could be possible in non-abnormal, yet overconfident, individuals.^(58,59)

Our additional analysis reveals that global (break-even) reference points exert less influence on the decision to cease trading amongst those who consistently experience profitable (or unprofitable) trading. In addition, our analysis exploring both global and local break-even points suggests that when possibly stronger NMM are developed (based on a larger number of months where a trader experiences more than 90% of these in loss) the effect of both global and local reference points are reduced. However, while those with stronger PMM appear to be less affected by global break-even effects, they appear to be more affected by local break-even effects.

Whilst this additional analysis suggests some interesting differences between the effects of local and global break-even points, there are some important issues that need to be considered in relation to these results. The first is that the changes in definitions may have led to these different groups having different levels of experience. For example, whilst we know that those in the 36- and 6-month groups (i.e. have experienced net profit or loss in more than 90% of the last 36 or 6 months, respectively) have certainly traded for at least 36 and 6 months, respectively, it is very difficult to control for trading experience. This arises because an individual might have engaged in trading prior to their first trade recorded with this particular brokerage. It is a potentially important issue, as trade experience could certainly play a role in the effects observed. It could therefore be misleading to draw any conclusions using a proxy of trading experience that is based on the length of time trading with this particular brokerage. Consequently, while these initial findings are certainly interesting, a convincing control variable for trading experience would need to be developed before firm conclusions could be drawn. In our main analysis, for the same reasons as those indicated above, we also could not control for trading experience. This, therefore should be considered a limitation of our study and it offers a valuable future direction if alternative data becomes available.

This study points towards the importance of considering a global break-even point as exerting distinct pressure on the decision to disengage in a RA. However, it is still unclear whether this is more or less important than local (recent) break-even points. It may be that there are individual differences whereby some individuals only consider the global break-even point while others focus more on recent changes in wealth. Alternatively, individuals may consider both at the same time, perhaps applying some form of weighting to the global and local break-even points. Whichever is the case, it is clear that there has been a failure of past research to consider the role of global break-even points in risk decisions.

5. CONCLUSION

This study extends previous research that has analyzed empirical data to explore the way in which individuals in real markets behave with respect to past profits and losses.⁽⁷³⁻⁷⁶⁾ Our results are consistent with the general finding that individuals employ mental accounting processes to deal with loss information. Our results suggest that the decision to disengage from an RA depends on recent changes in wealth around the global break-even point and how this recent information is interpreted in relation to an individual's mental model (developed by engaging in the RA).

Our results add to the wealth of studies that reveal how the context in which new information is received can affect its interpretation and subsequent behavior.⁽⁷⁷⁻⁸⁰⁾ Indeed, we propose that a history of past success and/or overconfidence could be important factors in dealing with chasing behavior. For example, overconfidence has often been associated with a higher trade frequency.⁽⁸⁰⁾ As such, institutions or regulators charged with managing traders who might be at risk of becoming rogue traders might consider examining their frequency of trades. Those with particularly high trade frequencies are at greater risk of trading longer than they ought in a market that is ultimately unprofitable for their strategy. At worst, these individuals may also be more susceptible to the risk of becoming a rogue trader, and this can cost financial institutions and the taxpayer significant sums of money.

Our findings reveal that there exist non-pathological cognitive processes (i.e. both local and global break-even effects) that can predict a tendency to continue with a RA despite experiencing consecutive periods in loss. A rational decision to take risks ought to be based on fundamental information about the risk and return payoffs. However, we find that it is also influenced by a motivation to break-even, not only based on recent experience in the RA but across an individuals' entire history of engaging in that RA . Clearly, such behavior could be detrimental to an individual's longer-term financial well-being. We suggest that evidence of overconfidence (e.g., excessive risk taking/investment/trading/gambling frequency) by an individual could provide an early indication of their susceptibility to future chasing behavior and an aversion to stopping a RA when in loss. Interventions for those who take financial risks, such as financial traders, gamblers, and even finance directors and professional investors, may help to reduce the impact of this particular phenomenon.

Our results also have important implications for understanding the efficient operation of markets. Several authors have discussed the idea that individuals may be forced to stop trading by losing money.⁽⁶⁰⁻⁶³⁾ The Adaptive Markets Hypothesis (AMH) is based around this theme and suggests that evolutionary processes force out the least successful traders, thereby leading to greater market efficiency, which is needed for a better allocation of resources in an economy.^(64,65) There is considerable debate concerning the veracity of the AMH. Simulation studies have shown that these evolutionary forces can be excessively slow (e.g., even if traders' beliefs differ significantly from the truth, simulations show that it can take a lifetime before an investor loses even half of their wealth).⁽⁶⁶⁾ However, several empirical studies have found support for the AMH.⁽⁶⁷⁻⁷²⁾

Our study presents new insights supporting the evolutionary process underpinning the AMH. In particular, we found that the decision to discontinue a RA is not just determined by the magnitude of losses incurred. Rather, it is also affected by the individual's longer-term performance and by cognitive biases associated with changes in wealth around the break-even point. This means that individuals can stop as soon as they fall below the break-even point (i.e.

after only very small losses). As a result, the evolutionary processes proposed in the AMH could foreseeably occur far more quickly than previously suggested, enabling rapid changes in market efficiency and improved resource allocation.⁽⁶⁶⁾

While there has been a considerable amount of research investigating the decision to take risks (versus choosing a non-risky alternative) or how risk information is communicated, very little research has investigated the factors that influence the decision to stop engaging in a risk-taking activity. This topic is particularly relevant when developing strategies and regulations for dealing with problem gamblers, whose difficulty in stopping gambling activity has detrimental effects on themselves and the people around them. It is also relevant to the analysis and prevention of rogue traders in financial markets whose behavior can affect entire businesses and potentially trigger economic events. Furthermore, the results may have important implications for all those engaged in any form of risk taking, including for example smoking, unprotected sex, alcohol use, illegal substance abuse, criminal activity and dangerous driving. The manner in which individuals might define and view break-even points in these non-financially focused risky activities is clearly a complex area for future research. However, it is clear from the results presented here that those interested in tackling these societal issues may need to consider the important roles that both global and more short-term break-even points play in the decisions to cease these risky activities.

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Appendix A: The Extended Cox Proportional Hazard Model

The CPH allows us to investigate the probability distribution of individuals ceasing to trade at time t , assuming they had not ceased trading before time t . This is particularly useful, since characteristics (e.g. profitability) associated with individuals may change in value through time (Chen et al., 2009). Furthermore, a CPH model enables us to employ partial information concerning traders, using censoring techniques, where the event (e.g. ceasing to trade) has not yet occurred. We defined the event that an individual ceased trading as the last recorded trade for this individual related to the market we investigated (FTSE futures). However, it is possible that an individual continued trading beyond the final date in our sample (17th April 2013). Therefore, we ‘right censored’ those individuals whose last recorded trade was regarded as sufficiently close to the final date that they may have continued trading. As a result of being right censored, they contribute to the overall calculation of the survival function up until the end of our records and are not classed as having ceased trading on their final trade date. We decided to right censor where the date of the last trade (n) for individual k ($Date_k^n$), was after 1st January 2012 (i.e. we only classified individuals that had not traded in over a year (15 months) as having ceased trading). This was considered reasonable, since the median individual traded 0.84 times (mean = 1.61) per day and only one individual in our sample (0.019%) had a time between opening and closing a trade greater than 12.9 months.

To examine the factors which influence the time until an individual ceases trading, we defined the hazard rate $h(t, \mathbf{x}_k(t))$ as the instantaneous probability of individual k ceasing to trade at month m ($t=m$, conditional on the ‘cease trading’ event not taking place before t) where variable $\mathbf{x}_k(t)$ represents a set of time-varying characteristics (e.g. returns) for trader k . Fisher and Lin (1999) showed that $h(t, \mathbf{x}_k(t))$, for the time-varying CPH model, is a log-linear function of a set of covariates $\mathbf{x}_k(t)$ and a baseline hazard, $h_0(t)$ as follows:

$$h(t, \mathbf{x}_k(t)) = h_0(t) \exp \left(\sum_l^n \beta_l' \mathbf{x}_k^l(t) \right), \quad (A1)$$

where $h(t, \mathbf{x}_k(t))$, is the time-dependent hazard function for individual k at time t , $\mathbf{x}_k^l(t)$ is the value of the l th ($l = 1, 2, 3 \dots N$) covariate at time t for individual k and β_l are the corresponding coefficients for $\mathbf{x}_k^l(t)$ for measuring the impact of the explanatory covariates on the hazard function.

The baseline hazard $h_0(t)$ describes how the risk event of ‘individuals’ cease-trading per time unit’ changes over time at the baseline level of covariates (when $\mathbf{x}_k^l(t)$ equals zero). By using such a CPH model, individual k ’s trading characteristics are included as explanatory covariates in $\mathbf{x}_k^l(t)$.

Using the hazard function introduced in Equation (A1) and assuming that there is only one ‘cease trading’ event occurring at t_k , the probability that individual k will cease trading at time t_k , $P_k(t + \Delta t > t_k \geq t | t_k \geq t)$ noted as P_k , can be represented by $h(t, \mathbf{x}_k(t))$ divided by the sum of all the hazards. This sum of hazards is represented by $\sum_{j: t_j > t_k} h(t, \mathbf{x}_k(t))$ at time t_k for the individuals (including k) who were at risk at t_k and where trader j ceases to trade at a time greater than t_k (i.e. $t_j > t_k$: all traders who have started to trade and have not yet ceased at time t_k). In other words, $j: t_j > t_k$ represents the set of individuals, $R(t_k)$ at risk of ceasing to trade at time t_k . According to Equation (A1), in which a hazard function for any individual trader is represented by the baseline hazard and the covariates, P_k can be represented as follows:

$$\frac{h_0(t) \exp\left(\sum_l^n \beta_l' \mathbf{x}_k^l(t)\right)}{\sum_{j: t_j > t_k} h_0(t) \exp\left(\sum_l^n \beta_l' \mathbf{x}_k^l(t)\right)} = \frac{\exp\left(\sum_l^n \beta_l' \mathbf{x}_k^l(t)\right)}{\sum_{j: t_j > t_k} \exp\left(\sum_l^n \beta_l' \mathbf{x}_k^l(t)\right)}. \quad (A2)$$

In Equation (A2), the numerator is proportional to the risk of individual k ceasing to trade at t_k , and the denominator is proportional to the total risk of ceasing to trade of all individuals j in the risk set $R(t_k)$. In addition, we adopted standard partial likelihood estimation methods to estimate the coefficients (β_l) in the time-varying CPH model.^(48,49)

We derive a set of coefficients (β_l) for each covariate, to indicate the change in the likelihood of ceasing to trade, based on the covariate values. For example, given a value for

covariate $\mathbf{x}_k^l(t)$ for a particular individual, say $\mathbf{x}_k^l(t) = 1$, and a coefficient for that covariate of $\beta_l = 0.1$, the hazard (of this individual ceasing trading) compared to the baseline (i.e., where $\mathbf{x}_k^l(t) = 0$), is $\exp(0.1 \cdot 1) = 1.105$ at time t . In other words, compared to an individual with $\mathbf{x}_k^l(t) = 0$, this trader has a 10.5% higher likelihood of ceasing trading at t , assuming that they have not ceased trading before t . A negative covariate, e.g., $\beta_l = -0.1$, would result in a reduced likelihood of ceasing to trade. In this case $\exp(-0.1 \cdot 1) = 0.905$, indicating that this individual has a 9.5% lower likelihood of ceasing to trade at time t , compared to a trader with $\mathbf{x}_k^l(t) = 0$.

Table I. How combinations of the $GenerallyProfitable_{km}$, $StatusChange_{km}$, and $NetLoss_{km}$ are used to indicate an individual's mental model (based on their long-term profitability) and events related to their trading activity.

Description	$GenerallyProfitable_{km}$	$StatusChange_{km}$	$NetLoss_{km}$
Positive mental model and has recently broken even, changing from net loss in month $m-1$ to net profit in month m .	1	1	0
Negative mental model and recently broken even, changing from net loss in month $m-1$ to net profit in month m .	0	1	0
Positive mental model and has recently fallen below the break-even point, moving from net profit in month $m-1$ to net loss in month m .	1	1	1
Negative mental model and has recently fallen below the break-even point, moving from net profit in month $m-1$ to net loss in month m .	0	1	1
Positive mental model, is currently in net profit in month m and was in net profit in month $m-1$.	1	0	0
Negative mental model, is currently in net profit in month m and was in net profit in month $m-1$.	0	0	0
Positive mental model, is currently in net loss in month m and was in net loss in month $m-1$.	1	0	1
Negative mental model, is currently in net loss in month m and was in net loss in month $m-1$.	0	0	1

Table II. Descriptive statistics for all the variables in the Cox survival model. Figures in the table show the mean (standard deviation) of each monthly variable across all traders aggregated by the year. Extreme values for a given period (i.e. those significantly different from the average across all remaining periods (tested via a Bonferroni adjusted t-tests)), are indicated by the following asterisk notation: $p < .001 = ***$, $p < .01 = **$, $p < .05 = *$.

Period	<2006	2006	2007	2008	2009	2010	2011+
Exit Rate (%)	60.5(49.0)	52.9(50.0)**	61.7(48.6)	68.8(46.3)***	75.8(42.8)***	62.4(48.5)	42.4(49.4)***
Return (%)	-5.5(18.0)	-5.4(28.1)	-4.0(17.2)	-3.5(43.9)	-4.4(16.8)	-4.9(24.7)	-4.6(18.5)
Volatility (%)	11.0(8.2)	11.4(10.8)	11.6(11.2)	14.0(18.6)***	11.8(18.7)	11.8(12.7)	12.1(11.9)
Total Return	-253.4(1444.8)	-242.3(1055.4)	-157.9(2044.1)*	-182.6(2725.1)*	-194.6(2597.2)*	-634.2(4324.6)*	-527.3(5045.3)*
Total Margin	7,454(25419)***	11,577(65,180)***	32,468(175,756)*	41,802(231,936)	43,130(254,941)	86,224(445,522)*	71,601(890,137)
ROI	-0.053(0.181)	-0.055(0.278)	-0.036(0.163)	-0.023(0.420)	-0.036(0.152)	-0.033(0.272)	-0.029(0.168)
Profit ROI	0.070(0.123)	0.054(0.113)	0.062(0.124)	0.058(0.161)	0.047(0.102)***	0.050(0.137)	0.060(0.136)
Loss ROI	-0.177(0.199)	-0.173(0.201)	-0.155(0.175)	-0.148(0.172)	-0.142(0.167)*	-0.146(0.181)	-0.151(0.167)
Generally Profitable	0.287(0.454)	0.240(0.428)	0.265(0.441)	0.282(0.450)	0.278(0.448)	0.255(0.436)	0.258(0.438)
Net Loss	0.359(0.428)	0.286(0.419)	0.310(0.416)	0.322(0.434)	0.315(0.433)	0.282(0.421)	0.283(0.413)*
Net Profit	0.641(0.428)	0.714(0.419)	0.690(0.416)	0.678(0.434)	0.685(0.433)	0.718(0.421)	0.717(0.413)*
Status Change	0.490(0.410)*	0.497(0.430)**	0.479(0.405)***	0.422(0.412)	0.420(0.414)	0.338(0.405)***	0.389(0.409)**
Stake	4.33(12.99)	3.88(13.21)	3.96(9.60)**	3.09(9.06)	2.88(8.33)	3.05(8.24)	2.72(6.34)**
Trades	4.2(4.8)***	6.2(11.3)***	15.4(35.0)	16.7(31.5)***	14.9(28.1)	14.5(31.0)	11.8(22.0)***
Hold Time (minutes)	2725(5800)	2792(9610)	1379(3973)***	1396(6065)***	1935(7041)***	4637(19440)**	4972(20933)***
Market Return (%)	0.045(0.095)***	0.031(0.102)***	0.009(0.097)***	-0.198(0.253)***	0.046(0.224)***	0.006(0.157)***	-0.021(0.140)*
Market Volatility (%)	0.486(0.113)***	0.576(0.186)***	0.900(0.211)***	1.789(0.928)***	1.219(0.396)***	0.831(0.251)***	0.857(0.383)***
No. of trader months	387	548	2016	3314	3884	2633	5677

Exit Rate (%) is percentage of individuals whose last trade was recoded in a given month. **Return(%)** is the percentage return on capital at risk achieved by an individual trader during the month. **Volatility (%)** is the standard deviation of the return on capital at risk achieved by an individual trader during a month. **Total Return** is the total returns in GBP earned by an individual trader during a month. **Total Margin** is the amount of margin in GBP required in a month. **ROI** is the return on margin earned by an individual trader during a month. **Profit ROI** and **Loss ROI** are, respectively, the positive and negative returns on margin achieved by an individual trader over a month. **Generally Profitable** is a binary variable assigned one if the trader, up until that month, had experienced more than 50% of months in profit, and zero otherwise. **Net Profit** and **Net Loss** are binary variables assigned one if the trader finished the month in net profit and in net loss, respectively, since beginning trading, and assigned zero otherwise. **Status Change** is a binary variable assigned a value of one if the trader had changed profit status (e.g. from net profit in the previous month to net loss in the current month), and zero otherwise. **Stake** is the average stake (GBP) per trade of an individual trader over a month. **Trades** is the total number of trades placed by an individual trader for that month. **Hold Time** is the mean holding time of trades of the trader in the month. **Market Return (%)** is the daily percentage return of the market over the month and **Market Volatility (%)** is the standard deviation of the daily market returns during the month.

Table III. Estimated coefficients for the Cox Proportional Hazards Model for assessing the likelihood that an individual will cease trading in a given month.

	Coef	Exp(coef)	SE(coef)	z	Pr(> z)	
Return	-0.106	0.899	0.077	-1.369	0.171	
Volatility	-0.329	0.720	0.116	-2.838	0.005	**
GenerallyProfitable	2.722	15.208	0.232	11.738	< 2e-16	***
NetLoss	2.280	9.775	0.236	9.664	< 2e-16	***
StatusChange	2.419	11.237	0.264	9.149	< 2e-16	***
-sqrt(-LossROI)	-0.746	0.474	0.137	-5.446	0.000	***
sqrt(ProfitROI)	-0.183	0.833	0.217	-0.845	0.398	
log(Stake)	-0.111	0.895	0.020	-5.451	0.000	***
log(Trades)	-0.155	0.856	0.017	-9.143	< 2e-16	***
log(HoldTime + 1)	-0.158	0.854	0.010	-15.793	< 2e-16	***
s(MarketReturn)	0.043	1.044	0.017	2.507	0.012	*
s(MarketVolatility)	0.410	1.506	0.034	12.005	< 2e-16	***
Period2006	-0.090	0.913	0.134	-0.678	0.498	
Period2007	-0.110	0.896	0.113	-0.977	0.328	
Period2008	-0.218	0.804	0.115	-1.898	0.058	
Period2009	0.138	1.148	0.109	1.267	0.205	
Period2010	0.051	1.052	0.112	0.450	0.652	
Period2011+	-0.561	0.571	0.111	-5.061	0.000	***
GenerallyProfitable × NetLoss	-3.204	0.041	0.301	-10.650	< 2e-16	***
GenerallyProfitable × StatusChange	-4.300	0.014	0.442	-9.733	< 2e-16	***
NetLoss × StatusChange	-1.883	0.152	0.272	-6.930	0.000	***
GenerallyProfitable × NetLoss × StatusChange	3.985	53.769	0.503	7.923	0.000	***

Return is the percentage return on capital at risk achieved by an individual trader during a month. **Volatility** is the standard deviation of the percentage return on capital at risk achieved by an individual trader during a month.

Generally Profitable is a binary variable assigned one if the trader, up until that month, had experienced more than 50% of months in profit, and zero otherwise. **Net Profit** and **Net Loss** are binary variables assigned one if the trader finished the month in net profit and in net loss, respectively, since beginning trading, and assigned zero otherwise.

Status Change is a binary variable assigned a value of one if the trader had changed profit status (e.g. from net profit in the previous month to net loss in the current month), and zero otherwise. **-Sqrt(-LossROI)** is the negative square root of an individual trader's negative returns on margin invested in that month. **Sqrt(ProfitROI)** is the square root of an individual trader's positive returns on margin invested in that month. **Log(Stake)** is the log of an individual trader's average stake during the month. **Log(Trades)** is the log of an individual trader's total number of trades in the month. **Log(HoldTime + 1)** is the log of an individual trader's average holding period of trades during the month.

S(MarketReturn) and **s(MarketVolatility)** are, respectively, the standardized z score transformation of the average of the daily return and standard deviation of daily returns in that month. **Period[year]** are dummy variables indicating the year of the period in question.

Coefficient significance is reported as $p < .001 = ***$, $p < .01 = **$, $p < .05 = *$.

N = 18,459. Log likelihood ratio statistic, $\chi^2(22) = 2,569$, $p < .001$, $R^2 = 0.13$. Harrel's c-index (concordance) = 0.766 (se = 0.008).

Table IV. Model estimates (calculated from Table II) for the likelihood of ceasing to trade (hazard ratio, $h(t)$) relative to the reference group for generally profitable (PMM) and unprofitable traders NMM)¹ whose cumulative returns in the current month change from net loss to net profit, net profit to net loss, stayed in profit or stayed in loss. The estimates based on models defining the PMM and NMM groups as those achieving more than 50%, 75% and 90% of months since commencing trading which ended in a positive or negative accumulated return, respectively, are shown.

Long-Term Historical Profitability	Previous Month	Current Month	In profit/loss for >50% of months since commencing trading		In profit/loss for > 75% of months since commencing trading		In profit/loss for > 90% of months since commencing trading	
			$\log(h(t))$	$h(t)$	$\log(h(t))$	$h(t)$	$\log(h(t))$	$h(t)$
Profitable (PMM)	Loss	Profit	0.841	2.318	-11.816	0.000	-10.897	0.000
Profitable (PMM)	Profit	Loss	2.019	7.529	0.595	1.813	0.337	1.401
Unprofitable (NMM)	Loss	Profit	2.419	11.237	1.746	5.732	1.319	3.740
Unprofitable (NMM)	Profit	Loss	2.816	16.717	1.868	6.475	1.613	5.018
Profitable (PMM)	Loss	Loss	1.798	6.036	1.216	3.374	-11.040	0.000
Unprofitable (NMM)	Loss	Loss	2.280	9.775	1.809	6.104	1.486	4.419
Profitable (PMM)	Profit	Profit	-0.482	0.618	-0.593	0.553	-12.526	0.000
Unprofitable (NMM; Baseline)	Profit	Profit	0.000	1.000	0.000	1.000	0.000	1.000

¹ Traders are defined as generally profitable (unprofitable) if they achieved more (fewer) than 50%, 75% or 90% of months since commencing trading which ended in a positive (negative) cumulative return. PMM and NMM refer to the assumption of a more positive and negative mental model, respectively.

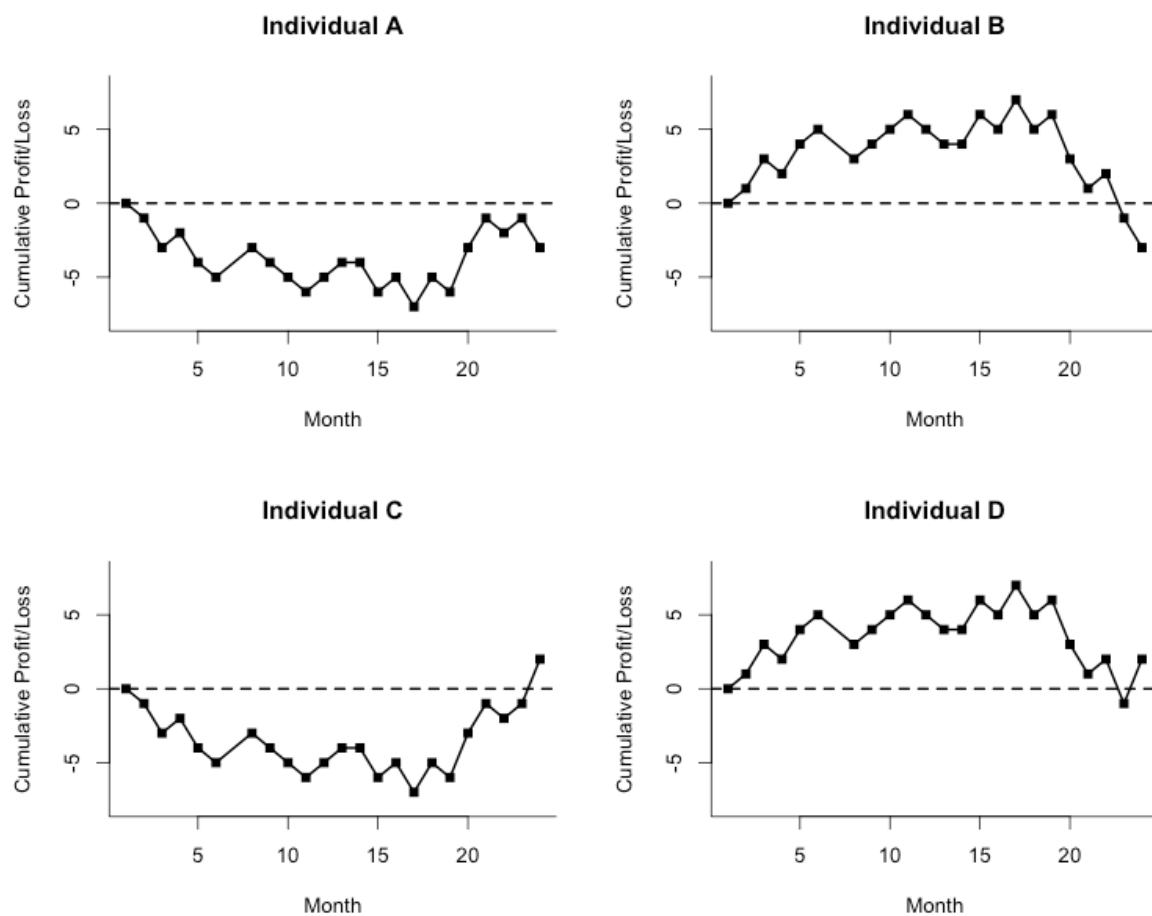
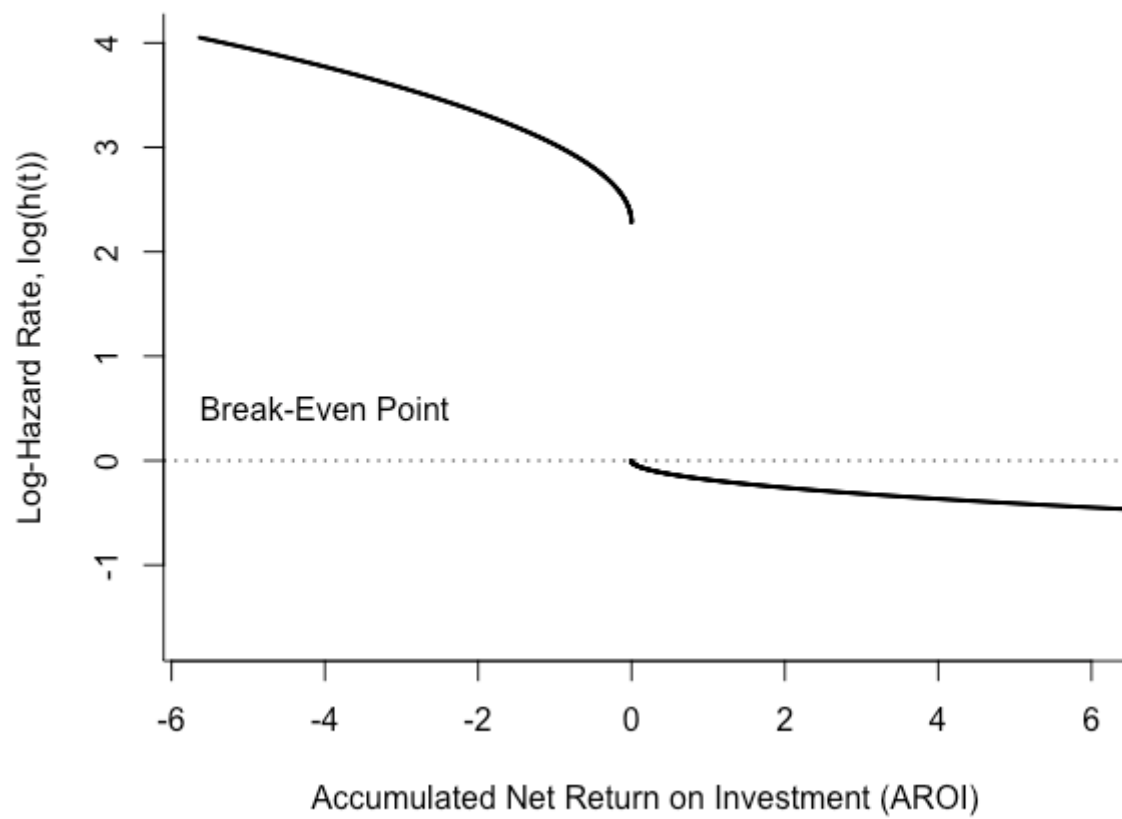


Figure 1. Four examples of histories of individuals engaged in a RA. Individuals A, B, C and D have the same negative net position as a result of their penultimate month of engaging in a RA. A and B remain in loss, whereas C and D move from net loss to net profit. A and C also have spent the majority of months engaged in the RA in net loss, whereas B and D have spent the majority of the months engaged in the RA in net profit.



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Figure 2. Log-hazard rate indicating the change in the likelihood of ceasing trading (likelihood increases as log-hazard rate increases) at various levels of net return on capital invested ($AROI_{km}$) relative to the break-even point.

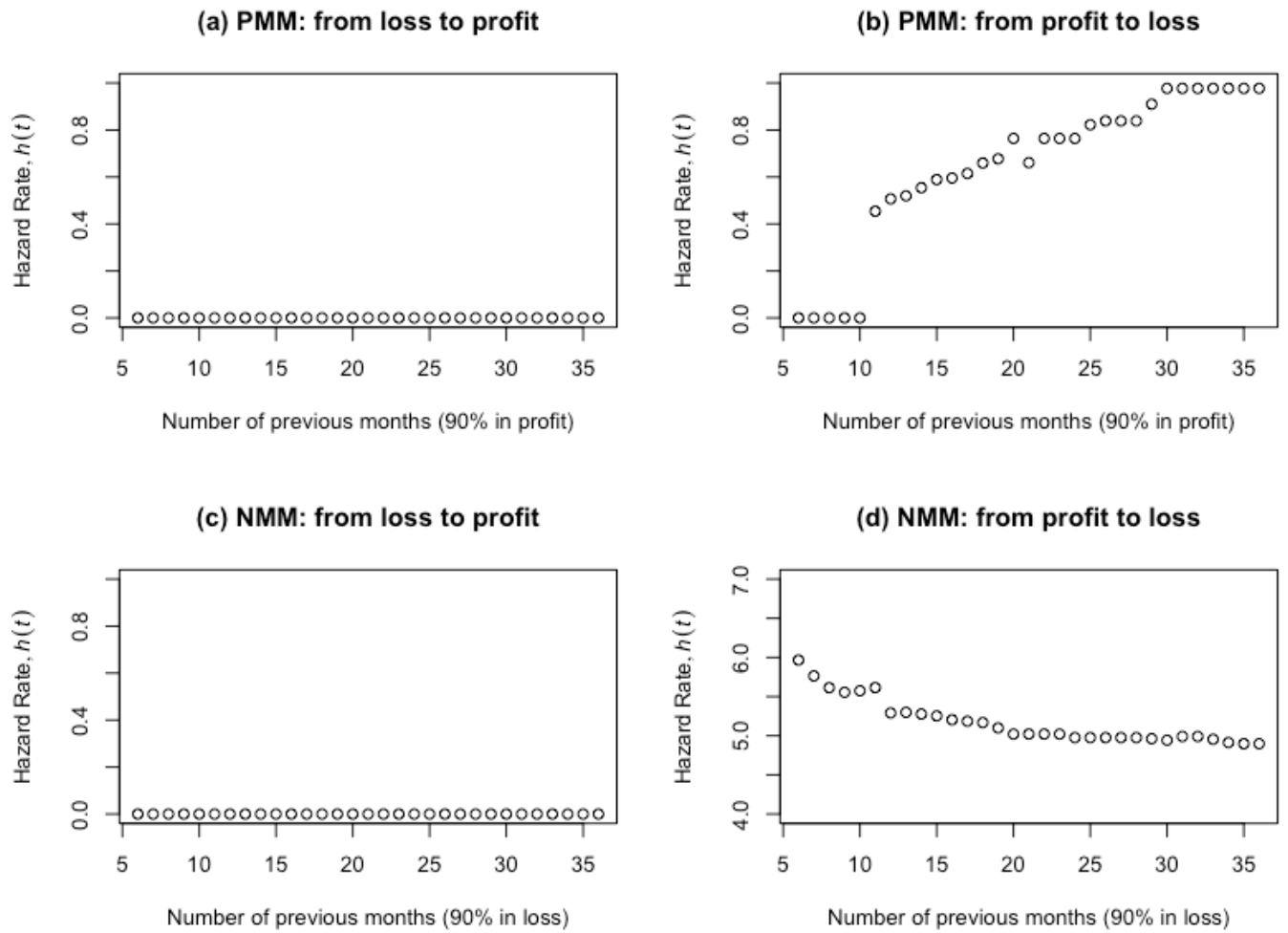


Figure 3. Hazard rate indicating the change in the likelihood of ceasing trading (likelihood increases as hazard rate increases) based on different definitions of long-term profitability. Figures a and b display the hazard rate changes for individuals that were profitable in more than 90% of (6 to 36) months prior to the current month. Figures c and d display hazard rate changes for individuals that were unprofitable in more than 90% of (6 to 36) months prior to the current month.